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Analysis

Integrated benefit-cost analysis of China's optimal adaptation and targeted mitigation

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ABSTRACT

In this work, we develop a regional integrated assessment framework by incorporating both adaptation and mitigation mechanisms to conduct benefit-cost analysis of China's optimal adaptation and portray the relative adaptation cost curve. In particular, we explore the influence of induced optimal mitigation, given the 2-degree warming-increase target, on the effectiveness of adaptation. Although adaptation alone may not be able to tackle all the risks of climate change, it remains a benefit-cost effective option. Our results show that China's optimal adaptation strategy can avoid, on average, 28% of climate damage over the entire simulation horizon. With respect to the reduction of adverse climate effects, the effect of a policy mix of both adaptation and mitigation does not appear to be "$1 + 1 \geq 2$", despite the combination strategy is still the better option compared to adaptation or mitigation alone. Robustness analysis reveals that the choice of time scales is important for policy effectiveness assessment, and the discount rate tells most of the story. Specifically, the lower the discount level, the higher the policy effectiveness; and the effectiveness of targeted policy would be significantly reinforced if a longer time scale is considered, given the same discount rate.

1. Introduction

Limiting the rise in global warming to below 2 degrees Celsius (°C) by the end of this century (relative to pre-industrial levels) has arrived at a consensus worldwide. During the COP 21 of the United Nations Framework Convention on Climate Change (UNFCCC) in 2015, this target was formally and legally included in the Paris Agreement (Nieto et al., 2018). To date, global average temperature has increased by over 0.8 °C, which implies that the achievement of this goal may be full of challenges (Parry, 2009; Peters et al., 2013), and the implementation of the Intended Nationally Determined Contributions (INDCs) mitigation plan of the Paris Agreement is hardly enough to keep temperature from exceeding the critical threshold (Reis et al., 2016). In this circumstance, it is of great necessity to start engaging in adaptation actions and coping with the climate residual damage that cannot be avoided by mitigation. In effect, with the indicators first covered in the Kyoto Protocol in 1997, restated in Bali conference in 2007, and then strengthened in Paris Agreement in 2015, the emphasis on the importance of adaptation as well as the interactive effect of both mitigation and adaptation has grown greatly (Bosello et al., 2010).

With respect to the world, specific countries or regions may suffer more acutely from the impact of global warming, owing to the significant differences in locations, climate adaptation capabilities and vulnerability (Baker et al., 2012; Schwirplies, 2018), which implies that adaptation may be even more promising in avoiding climate damages at the regional level (Lesnikowski et al., 2015; Araos et al., 2016). China has the world's largest population, with > 1.36 billion people in 2015 (approximately 18.8% of the world's total population). The size of the population yields a strong demand on output, consumption and energy sources. As a consequence, China contributes almost 1/3 of the world's GHG emissions, and this in turn poses an unprecedented pressure on emissions control. In addition, China possesses 1/15 of the world's geographic land area and has the longest land coastline, at approximately 18,400 km, which makes China more vulnerable to the risks of sea-level rise, storm activities and tsunamis, which in turn puts forward higher requirements for integrated coastal zone management (ICAM), disaster protection capability building, extreme climate event defense and emergency response mechanisms.

In effect, China has made adaptation an important part of the national strategy in response to climate change in its INDC plan and

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committed to accelerating implementation of the 'National Strategy of Climate Change Adaptation' (NDRC, 2015). On these bases, it is of great meaning to deeply explore the benefit-cost effectiveness (BCE) of China's optimal adaptation in avoiding climate change damages and empirically discuss the interactions between both optimal adaptation and mitigation under the given target.[1] In general, it is not difficult to assess the efficiency and effectiveness of emission reduction, and the corresponding evaluation systems and assessment standards are therefore relatively easier to develop (Ford and Berrang-Ford, 2015). When moving to adaptation, there are few ready-made standards, methods, indicators and baselines to evaluate adaptation effectiveness for some specific targets, especially for developing countries (UNFCCC, 2015). This is the main motivation behind this work; we believe our study will be largely beneficial for building domestic adaptation tracking system.[2]

To be specific, we have two main aims: the first is to develop an adaptation-incorporated integrated model based on the CE3METL. With this framework in hand, we then examine the optimal adaptation investment path and protection level and portray the optimal adaptation cost curve of China. Second, given the 2-degree temperature-limit target officially included in the Paris Agreement, we explore the possible impact of mitigation intervention on the effectiveness of adaptation. Specifically, we systematically compare the damage-reducing effect between adaptation and mitigation in the framework of benefit-cost analysis.

Recently, a rich body of literature has focused on climate adaptation, including at both the methodology level, such as the introduction and improvement of adaptation mechanism in integrated assessment models (IAMs), and the application level, such as adaptation efficiency analysis and the interactive effect between mitigation and adaptation (Wende et al., 2012; Evans et al., 2014; Zemel, 2015). Climate adaptation has been incorporated in IAMs since the beginning of 1990s, and Hope et al. (1993) first exogenized the adaptation as a scenario variable and conducted a relative cost-benefit analysis. After that, adaptation in IAMs experienced a developing process from implicit consideration to dependent explicit incorporation, and the included adaptation investment improves from pure flows to portfolios of both flows and stocks (de Bruin et al., 2009; Patt et al., 2010; Agrawala et al., 2011; Moore and Diaz, 2015).

Although adaptation has little relation with greenhouse gas (GHG) emissions reduction, it may substantially reduce the adverse effect of climate change, which has been validated by many studies (Bréchet et al., 2013; Schwirplies, 2018). Hope et al. (1993) noted that adaptation could avoid the climate damages of OECD countries and the rest of world by 90% and 50%, respectively. In contrast, de Bruin et al. (2009) argued that climate adaptation might relieve the pressure on emissions control by 25% and reduce climate damages by 33%; without catastrophic damages, the contribution of adaptation may be three-and-a-half-fold higher than that of mitigation (Bosello et al., 2010). Generally, mitigation is responsible for addressing basic climate damages by curbing GHG emissions, whereas adaptation mainly acts on the residual damages, and these two options are often complementary in response to climate damages reduction (Watkiss et al., 2015). From the policy perspective, the increase in the focus on adaptation does not mean a relative reduction of attention on mitigation (Carrico et al., 2015). However, given the limited investment budget, there appears to be a crowd-out effect of investment between adaptation and mitigation, and the damage-averting effect of each is significantly affected by the others' implementation (Zemel, 2015). In general, the crowd-out effect of adaptation on mitigation is much larger than that of mitigation on adaptation (Bosello et al., 2010; Agrawala et al., 2011). As for high adaptive countries, this crowd-out and substitution effect may not be significant (Tubi et al., 2012). It is worth noting that the effect of mitigation on climate damage reductions is more significant if a longer time period is considered, whereas in the short term, adaptation acts as the main contributor, especially for avoiding the specific damages resulting from a sea-level rise (Tol, 2009; Bréchet et al., 2013); even in 2130, the damage-reducing effect of adaptation is still higher than that of mitigation (de Bruin et al., 2009).

From the above literature survey, we find that the majority of the extant works study adaptation problems from a global perspective, and the scarcity of research focuses on regional adaptation; further, few research has been found to explore the impact of mitigation intervention under the Paris Agreement climate target on the effectiveness of optimal adaptation, especially based on the framework of benefit-cost analysis. This work will greatly contribute to fill this gap.

The rest of this work is organized as follows. Section 2 briefly introduces the Chinese integrated assessment model, CE3METL, with an emphasis on descriptions of the adaptation mechanism and adjustments of the climate module. In Section 3, we shortly show the introductions of key data and parameter, and model calibrations; then in Section 4, we present the main results and analysis. The last section concludes the paper.

2. Methodologies

This research is conducted by employing and developing the regional 3E-integrated assessment model, CE3METL (Energy-Economy-Environmental Model with Endogenous Technological change by employing Logistic curves) and the global 3E-integrated assessment model, E3METL. To be specific, we first run the CE3METL model to yield China's emission trajectories; second, we obtain the global emissions via optimizing the global model E3METL, then we could get the emissions out of China (rest of the world) by netting emissions between the globe and China; third, we view the emissions out of China to be exogenous in CE3METL when considering the policy scenarios. All the policy cases are implemented within CE3METL, and the emission cap is set in terms of inertia principle.[3] The basic framework and work route of this paper are schematically portrayed in Fig. 1.

E3METL, featuring a Logistic-based multi-technological diffusion core, was first developed in 2013 (Duan et al., 2013), and CE3METL is the regional version focusing on China (Duan et al., 2014); they therefore have similar model structures: being composed of economic, energy and climate modules, including fossil energy sector (coal, oil and natural gas) and non-fossil sector (biomass, hydro, nuclear, wind, PV solar, geothermal, tide technology), etc. In both E3METL and CE3METL, we attempt to adopt the revised Logistic curves to describe evolutionary dynamics of multiple energy technology, especially interactions between conventional carbon-based fuels and non-fossil energy technologies. Given share of non-fossil technology $S_{i,\ t}$ and its possible potential $\widetilde{S}_{i,t}$ $(0 < \widetilde{S}_{i,t} \leq 1)$, the multi-technological diffusion mechanism could be described as

$$\frac{\mathrm{d}S_{i,t}}{\mathrm{d}P_{i,t}} = \alpha_i S_{i,t}\left(\widetilde{S}_{i,t}\left(1 - \sum\nolimits_{j\neq i} S_{j,t}\right) - S_{i,t}\right) \quad (1)$$

where $P_{i,\ t}$ denotes relative costs of the marker technology (e.g. coal) to that of the targeted non-fossil technology i; and by taking into account

[1] In this paper, we discuss the policy effectiveness in the benefit-cost framework, so the phrase 'effectiveness, appears in the whole text refers to benefit-cost effectiveness (BCE), unless otherwise mentioned. Besides, we distinguish 'effective' from 'benefit-cost effective' in specific expressions.

[2] An adaptation tracking system provides adaptation monitoring and evaluation and particularly seeks to systematically identify, characterize and compare adaptation effect across nations and over time (Ford et al., 2015).

[3] The emission-allocating principles, such as grandfathering (inertia), equality (GDP per capita) and blended principles, may play formidable roles in analysis of benefit-cost ratios of China's climate actions, but this is out of the scope of this work and it actually has been discussed in one of our previous papers (Duan et al., 2018).

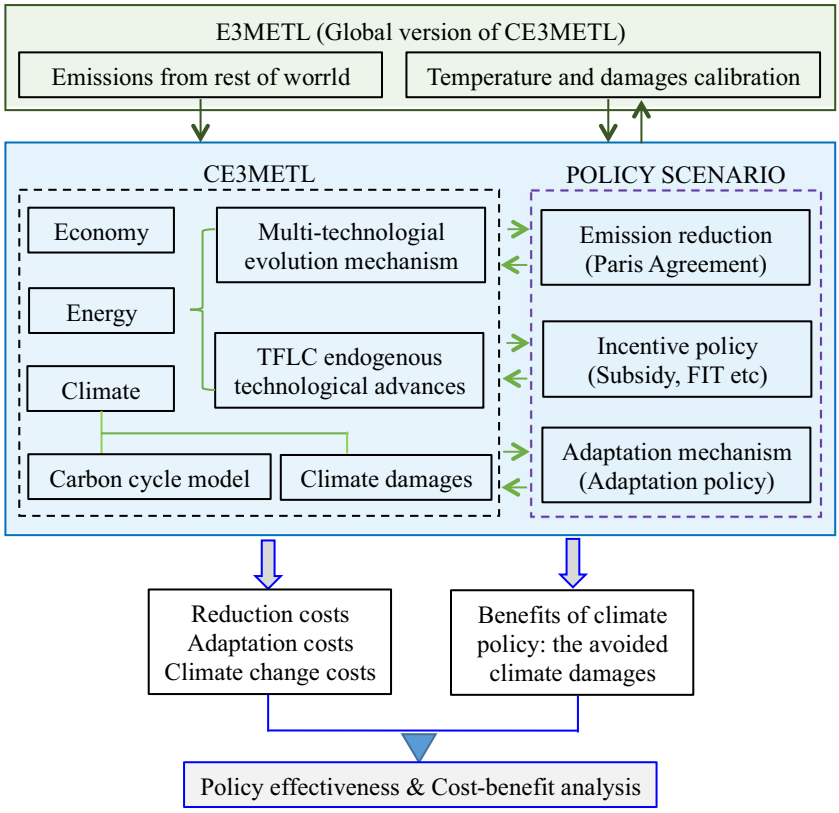

Fig. 1. Schematic framework of this work.

the rates of carbon tax ($Tax_{coal,\,t}$) for the marker technology and subsidy ($Sub_{i,\,t}$) for the alternative i, we give $P_{i,\,t}$ as below

$$P_{i,t} = \frac{C_{coal,t}(1 + Tax_{coal,t})}{C_{i,t}(1 + Sub_{i,t})} \tag{2}$$

here $C_{i,\,t}$ is the unit cost of alternative technology i. It is easy to find that the revised Logistic model will reduce to the original one, if the relative cost $P_{i,\,t}$ equals to time step size Δt and technology potential $\widetilde{S}_{i,t}$ equals to 1. Formula (1) and (2) indicate that the diffusion of alternative technology i accelerates as the relative cost ($P_{i,\,t}$) increases and the stringency of carbon tax ($Tax_{coal,\,t}$) enhances. More details on the rationale behind the revised Logistic curves could be refereed to Anderson and Winne (2004) and Duan et al. (2015).

Through incorporating the revised Logistic model into the energy module of CE3METL, we could better describe the dynamic evolution of multiple energy technologies (Duan et al., 2015). The detailed advantages of this model innovation could be summarized as follows: first, the original Logistic curve has been proven to fit very well with the inner "S-sharped" rules of technology diffusion (Romeo, 1977), therefore, the updated Logistic curves should be more rational to consider dynamic multi-technological evolution (Anderson and Winne, 2004); second, energy costs are one of important factors that significantly affect the diffusion of alternative technologies, on this basis, it is a highlighted innovation for us to incorporate the cost-induced new technological mechanism into the typical IAM framework; third, compared to the traditional constant elasticity substitution (CES) function method, the Logistic-based mechanism largely facilitate the incorporation of multiple energy technologies with more simplified structures (interactions between any couple of energy technologies could be alternatively described by interactions between the marker technology and each targeted technology, while leaving out the multiple levels of nesting as in CES method), which conveniently allow us to enrich the technical details of conventional top-down IAMs (Duan et al., 2015). For more details on this new technology mechanism and the original CE3METL, please see Appendix A in Supplementary Information (SI) file.

Generally, adaptation means a series of measures that directly or indirectly reduce the vulnerability of the natural ecological and human social systems, and some proactive and protective actions to avoid climate damages are also included (Dumas and Ha-Duong, 2013). CE3METL defines adaptation as a dependent explicit variable, and adaptation capability comes from both investment flows and stocks, which allows the adaptation investment and the relative adaptation effect to occur in different time periods (Agrawala et al., 2011; Bosello and De Cian, 2014).[4] Referring to Agrawala et al. (2011), we assume that adaptation investment flows and stocks are imperfectly substitutable. Then, we can employ the CES method to describe the relationships between these two types of adaptation actions. To be specific, we denote the adaptation capability $ADAP(t)$, then it could be formulated as below:

$$ADAP(t) = \xi_1(\xi_2 I_{rfa}(t)^{\xi_3} + (1 - \xi_2)K_{pas}(t)^{\xi_3})^{1/\xi_3}, \tag{3}$$

where ξ_1 is the scare factor and ξ_2 and ξ_3 represent the share of reactive adaptation investment and the substitution elasticity between adaptation flow investment and proactive stock. $I_{rfa}(t)$ and $K_{pas}(t)$ correspond to the reactive flow investment and the proactive adaptation stock, respectively, and this stock is the sum of the depreciated adaptation stock in the previous period and the new-added proactive investment, i.e.,

[4] Flow adaptation here mainly refers to the reactive actions, and the investment and benefit appear in the same period, e.g., purchasing air conditioners to respond to the hot days, whereas stock adaptation means some proactive adaptation actions, e.g., building dykes and sea walls and updating crop types, irrigation and the use of mosquito nets to limit the spread of diseases. In addition, because of the unavailability of detailed separated data, we did not take the generic adaptive capacity into account, and the specific capacity investment is merged into the proactive stock investment.

$$K_{pas}(t) = (1 - \delta_{pas})K_{pas}(t-1) + I_{pas}(t), \quad (4)$$

here δ_{pas} is the depreciation rate of adaptation stock accumulation and is assumed to be equal to that of the physical capital stock.

CE3METL adopts the DICE damage function to consider the relations between the warming-rise and climate response damages; that is, we assume that the relationship is quadratic, without taking the sharp threshold and tipping points into account. Specifically, we denote the damage coefficient $\varphi(t)$. Then the impact of global warming on output can be portrayed as follows (Lemoine and Kapnick, 2016):

$$Y_N(t) = \frac{1}{1 + \varphi(t)} Y(t), \quad (5)$$

and

$$\varphi(t) = \zeta_1 \Delta T + \zeta_2 \Delta T^{\zeta_3}, \quad (6)$$

where $Y(t)$ and $Y_N(t)$ are China's gross output and output net of climate damages.[5] In the absence of mitigation and adaptation, the gross damage $D_G(t)$ is equivalent to the residual damage, and the gross damage $D_G(t)$ can be calculated as follows:

$$D_G(t) = Y(t) - Y_N(t) = \varphi(t) Y_N(t). \quad (7)$$

Obviously, the adoption of the DICE damage function determines that the gross climate damage never exceeds the gross output, which implies that this method is not suitable for describing catastrophic climate damages (Nordhaus and Sztorc, 2013).

If adaptation is undertaken, then the damage coefficient becomes the following:

$$\varphi'(t) = \frac{1}{1 + ADAP(t)} \varphi(t), \quad (8)$$

and the residual damages are now calculated as:

$$D_R(t) = \varphi'(t) Y_N(t) = \frac{1}{1 + ADAP(t)} \varphi(t) Y_N(t). \quad (9)$$

Thus, if the adaptation level approaches zero, then the damage coefficient $\varphi'(t)$ reduces to $\varphi(t)$; if the adaptation level approaches infinity, then the residual damage tends to zero. Additionally, given the adaptation costs $ADC(t)$, we can obtain the adaptation benefits (i.e., avoided climate damages) as below:

$$D_B(t) = D_G(t) - D_R(t) - ADC(t), \quad (10)$$

and the adaptation cost is defined as the sum of all types of adaptation investment, i.e.,

$$ADC(t) = I_{rfa}(t) + I_{pas}(t). \quad (11)$$

3. Model calibrations

In this section, we calibrate the model surrounding the climate response damages and adaptation. Similar to the other modeling works, we choose a point doubling of the CO_2 concentration as our calibration point (de Bruin et al., 2009; Agrawala et al., 2011, etc.), and in the framework of DICE2016, a doubling of the CO_2 concentration equivalent to a warming-rise of 2.5 °C. Based on the climate sensitivity parameter referring to DICE2016 and the estimated CO_2 emission path via optimization of E3METL, we calculate the trajectory of the global warming rise, and the specific value in 2100 is approximately 3.7 °C (relative to the 1900 level), which is highly consistent with the estimation of WITCH and slightly lower than the DICE result of 3.85 °C (Nordhaus and Sztorc, 2013; Bosello and De Cian, 2014). How to systematically assess the adverse effect resulting from climate change, including both market damages and non-market damages, has long been the difficulty in the modeling work of IAMs. Tol (2009) surveyed the related studies and found that the gross climate damages at the calibration point range from −1% and 2.5% of the output. In effect, it is even more difficult to evaluate the regional climate damages, especially for China, and to date, scant attempts seem to have been made. Essentially, the assessment of climate damages in IAMs is determined by the coefficients of damage function. Table 1 summarizes the coefficients of the DICE function across various studies. DICE-2R divides the world into two regions, i.e., the rich region and the poor region; thus, the corresponding parameter values are not specific to China but the average level of the poor region (Moore and Diaz, 2015). RICE2010 views China as an individual region, and we can directly obtain the relative parameter values from the model, but the coefficients seem to be outdated, as the estimated damage at the calibration point is over the upper bound of surveyed range (i.e., 2.5%). We therefore calibrate the coefficients of damage function in CE3METL by referring to the latest DICE model, i.e., DICE2016 (Nordhaus, 2017). Actually, climate damages at the calibration point is still higher than the upper bound of surveyed damages in China (i.e., 1.92%), given the original coefficients of damage function in DICE2016, that's why our parameter value ζ_2 is calibrated to be a little lower, and the effects under this group of parameter values are largely in line with the previous version of RICE model, i.e., RICE1999 (Nordhaus and Boyer, 2000).

Based on the coefficient inputs shown in Table 1, we get China's climate damage at the calibration point, i.e., 1.12% of GDP, and it is greatly consistent with the estimation of DICE, MERGE and WITCH, in which the projected climate damage interval of China is between 0.17% and 1.92% (percentage GDP) (Bosello and De Cian, 2014). And by 2100, this damage ratio resulting from climate change will increase to 2.36% (Fig. 2). In order to further explore the effects of key coefficients of damage function, we conduct a detailed sensitivity analysis in the last part of results (see Section 4.3.2).

The adaptation investment data for both the flow and stock are abstracted from China's Environmental Statistical Yearbook (NBS, 2011), and the imperfect substitution elasticity refers to WITCH (σ=1.2). Further, the investment expenditure for the reactive adaptation actions and proactive adaptation actions at the calibration points comes from Bosello and De Cian (2014).[6] On this basis, we obtain the calibrating adaptation investment paths, as illustrated in Fig. 3. Based on the investment flows, the reactive investment and proactive investment will grow to 130.6 and 223.2 billion US dollars (USD), respectively, by 2100, accounting for approximately 0.025% and 0.03% of GDP; as for the cumulative results, as portrayed by the bar chart embedded in Fig. 3, the total reactive investment and proactive investment will account for 0.047% and 0.066% of the total GDP, respectively in 2100.

In addition to the adaptation investment, the trajectory of the adaptation protection level is closely related to the calibration of adaptation parameters; here the protection level is defined as $(D_G(t) - D_R(t))/D_G(t)$. Bosello and De Cian (2014) systematically estimated the protection level associated with climate adaptation at the calibration point, involving agriculture, coastline protection, infrastructure and the ecosystem, and gave the corresponding results as the simple average, average weighted by the damage share and average weighted by the protection cost levels, i.e., 0.44, 0.21 and 0.39. On this

[5] The climate damages measured here do not cover the non-market damages associated with biodiversity, ocean acidification, political reactions, see-level rises, ocean-cycle changes and catastrophic disaster (Tol, 2009).

[6] Actually, it is difficult to separate the generic adaptation capacity from the specific capacity investment because of very limited data provided by China's Environmental Statistical Yearbook, and there is no records on China's historical adaptation protection level as well, which greatly restricts us to employ a more complex and informative adaptation mechanism to describe the optimal adaptation process in CE3METL. We therefore have to calibrate the simplified adaptation curve in terms of the available data in the initial year (2010), the first period (2015), and the climate damages at the calibration point.

Table 1
Cross-study comparisons of coefficients of DICE damage function.

	ζ_1	ζ_2	ζ_3	Geography	Sources
RICE1999	−0.0041	0.0020	2.000	China	Nordhaus and Boyer (2000)
RICE2010	0.0780	0.0126	2.000	China	Nordhaus (2010)
DICE-2R	0.0026	0.0022	2.000	Poor region	Moore and Diaz (2015)
DICE2016	0.0000	0.0024	2.000	Global	Nordhaus (2017)
CE3METL	0.0001	0.0017	2.000	China	Calibrated in this work

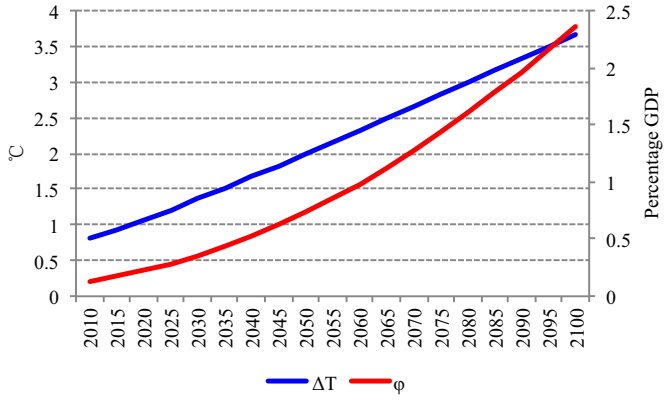

Fig. 2. Paths of temperature-rise and damage rate after model calibration.

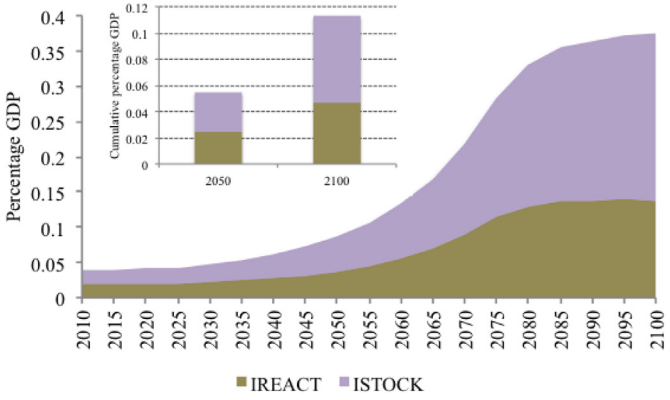

Fig. 3. Optimal adaptation investment paths and evolution of relative investment construction.
Note: IREACT and ISTOCK represent the reactive adaptation investment and proactive stock investment, respectively; the embedded subfigure gives the cumulative results in 2050 and 2100, with a 5% discount rate.

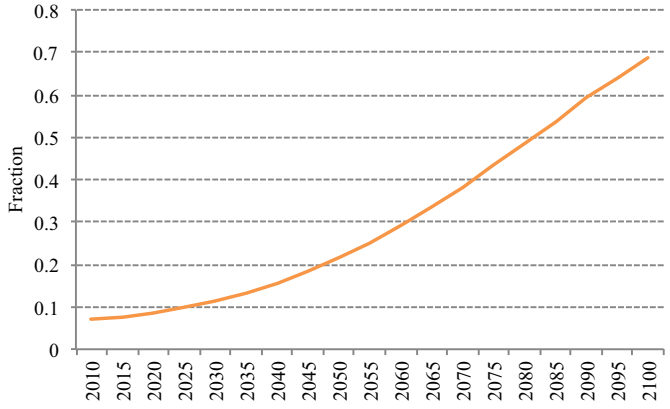

Fig. 4. Calibrated optimal protection level of adaptation.

ground, we estimate the protection level at the calibration point to be 0.33, and the dynamic route of optimal protection level for China is shown in Fig. 4, from which we can observe that China's optimal protection level of adaptation in 2050 is 0.215, and adaptation protection will be largely reinforced to 0.689 by the end of this century.

Based on the baseline scenario, we provide several basic comparisons between our results and those in the related model works in terms of critical model indicators, such as GDP, emissions and warming-rise, which should be helpful to understand all the following results under adaptation and mitigation policies (see Appendix B and C in SI for details).

4. Results and discussions

In the results, we will first provide the dynamic adaptation cost curve under the optimal adaptation investment. Then, we try to analyze the evolutionary relations between the gross damages and the residual damages. Second, we introduce the optimal mitigation policy under the Paris Agreement climate target (i.e., 2 °C warming-rise limit goal) and explore the possible impact of mitigation intervention on optimal adaptation; further, great emphasis will be put on comparing the effectiveness of both adaptation and mitigation in the framework of benefit-cost analysis. It worth noting that as a single-region model, CE3METL does not allows us to capture the avoided damages associated with China's targeted mitigation in the other countries, and to some extent, this may cause underestimation of the resulting climate benefits. To this end, we design several policy simulation scenarios in addition to the reference case, including the optimal adaptation scenario, the targeted mitigation scenario and the policy mix of both adaptation and mitigation. The scenario set details are listed in Table 2.

4.1. The optimal adaptation and its benefit-cost effectiveness

In terms of model calibrations in Section 3, we calculate China's gross climate damages, residual damages, gross adaptation costs and climate change costs (the sum of the residual damages and adaptation costs) before 2100, as illustrated in Fig. 5-(a). As observed in this chart, the gross damages increase monotonically during the entire simulation horizon; in contrast, the trajectory of residual damages is not monotonic because of the effect of adaptation. More specifically, the residual damages stably decrease after 2075, and the decreasing trend is not monotonic. Actually, as the adaptation investment slows down in the latter period, the residual damages begin to rebound. Our simulation results show that the residual climate damages are 0.76% of GDP in 2070, gradually reduce to 0.72% in 2085, and then rebound to 0.8% in 2100. In addition, the climate change costs continue growing throughout the simulation, with the share in GDP growing from 0.71% in 2050 to 1.17% in 2100.

From the perspective of cumulative damages, the difference between gross damages and residual damages significantly increases as time progresses; specifically, this difference is just 0.03% of the GDP in 2050. When turning to the end of this century, it will expand to 0.23% (Fig. 5-(b)). In general, the adaptation investment action in the early period is not positive, and there are time lags before the adaptation stock accumulates and comes into effect. In the latter period, the active adaptation investment accelerates the accumulation of adaptation stock. Then adaptation efforts are gradually transferred to a growing protection level, which in turn directly reduces the climate damages. Thus, better adaptation effects require earlier protective investment, and this is true no matter at the global level or the regional level (Agrawala et al., 2011).

Given the gross damages and residual damages, as well as adaptation costs, we can obtain the optimal adaptation cost curve of China, as depicted in Fig. 5-(c), in which the horizontal axis gives protection level and the vertical axis shows the share of the adaptation costs to GDP. As expected, the protection level increases monotonically as the

Table 2
Scenario setting and details.

Scenarios	Descriptions
RES	**RE**ference **S**cenario, without any adaptation or mitigation actions taken into account; this is also called the no policy or business-as-usual (BAU) case, which is mainly used for reference and comparison
ADS	**AD**aptation **S**cenario, with optimal adaptation and without targeted mitigation (optimal adaptation here means no adaptation restrictions are considered)
MIS	**MI**tigation **S**cenario, with mitigation and without adaptation; mitigation is optimally implemented by introducing the Paris Agreement climate target (2°Cgoal)
ADMIS	**AD**aptation and **MI**tigation **S**cenario, with both optimal adaptation and 2-degree consistent targeted mitigation

Note: For the targeted mitigation scenario (MIS), we employ the loosest principle, i.e., grandfathering, to get China's cumulative emission space from the global emission cap that is consistent with the two degrees warming-limit targets (Raupach et al., 2014), and the optimal emission trajectories are yielded by endogenizing the social cost of carbon (SCC).

investment cost grows, from < 0.01% in the initial year to 0.15% in 2050 and further to 0.66% in 2100. In addition, the average protection level throughout the simulation horizon is approximately 0.28%, which means that the optimal adaptation effort could on average avoid 28% of China's gross climate damages, and this result is relatively lower than the corresponding estimation on the global scale, i.e., 33% (de Bruin et al., 2009). Therefore, even if no adaptation restrictions are considered, the protection level will be far from 100% by the end of this century, which demonstrates that adaptation alone is not enough to face all the climate change risks. Compared to mitigation, adaptation action should be understood as a type of 'compromise effort' because it does not directly cut emissions or control global warming, and over-investment in adaptation can even damage the positive damage-averting effect of mitigation (de Bruin and Dellink, 2011).

To primarily analyze the effectiveness of optimal adaptation, we depict the ratio of adaptation benefits to costs, as illustrated in Fig. 5-(d). It is easy to observe that the growth trend of adaptation effectiveness (BCE) is rather significant, and from 2050, the adaptation benefit starts to exceed the relative cost, with the rate of benefits to costs being 1.23. As adaptation efforts increase, the BCE of optimal adaptation grows rapidly, and by 2100, the benefit-cost rate expands to 4.17. It is important to mention that the estimated benefit-cost rate for China is still lower than the corresponding results on the global scale. For example, Hope et al. (1993) estimated that the global ratio of cumulative adaptation benefits to costs would be approximately 11.7 from 2000 to 2200, and PAGE2002's evaluation displayed that the rate of adaptation benefits to costs could even be as high as 60 (Parry et al., 2009).

4.2. The effect of mitigation intervention on adaptation

Mitigation is an indispensable option for coping with climate damage risk. To examine the impact of mitigation intervention on damage reduction and especially on adaptation effectiveness, we implement targeted mitigation in the present model framework; specifically, mitigation is optimally carried out by introducing the official climate target of the Paris Agreement, i.e., keeping the temperature rise below 2 °C relative to the pre-industrial level. We first report the path of China's CO_2 emissions and changes in emission-control rate, as shown in Fig. 6. In the reference case, China will peak its carbon emissions at approximately 2045, with a peak of 3.48 GtC (giga tons of carbon). Our baseline emission results should be understood based on two critical

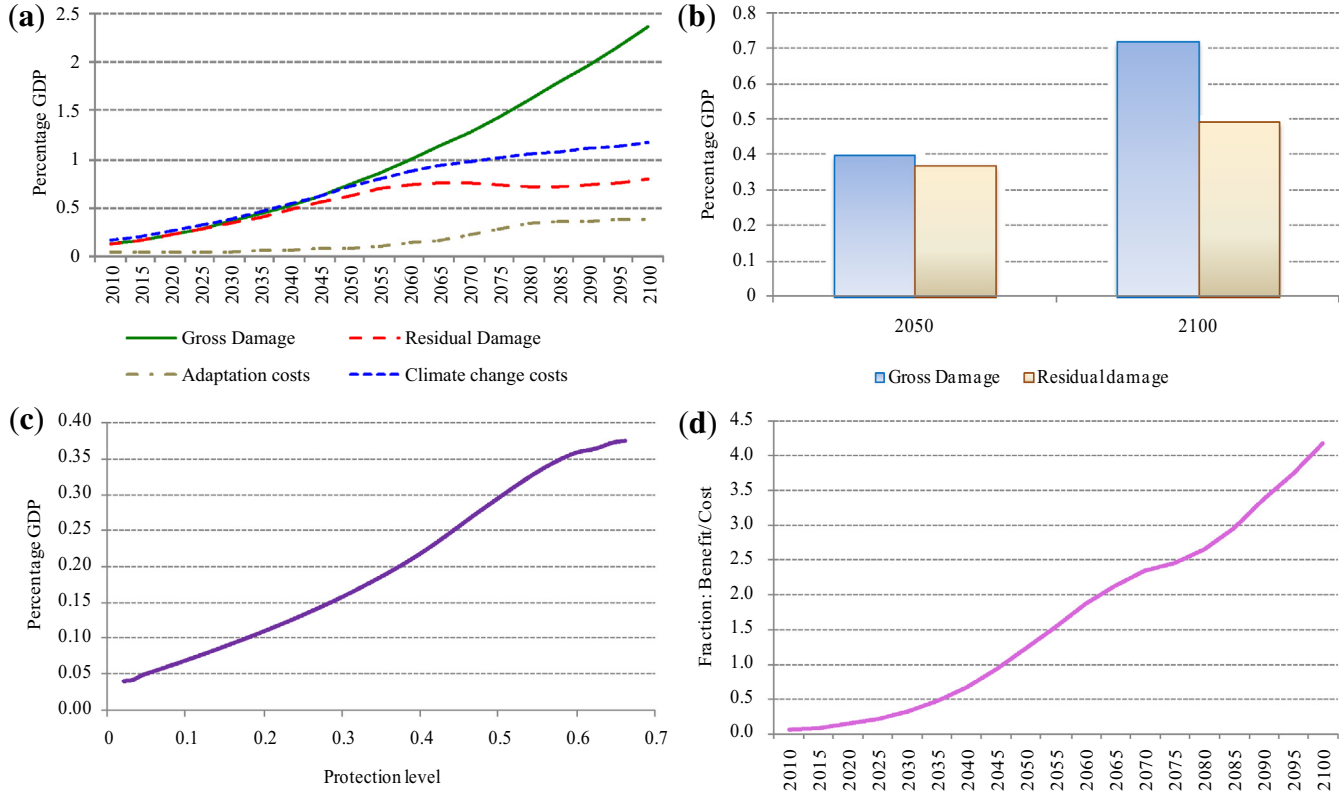

Fig. 5. Climate responses and protection level in the presence of optimal adaptation, (a) dynamic climate results of key indicators, (b) cumulative gross damages and residual damages in 2050 and 2100, (c) China's optimal adaptation cost curve and (d) changes in the benefit-cost rate.

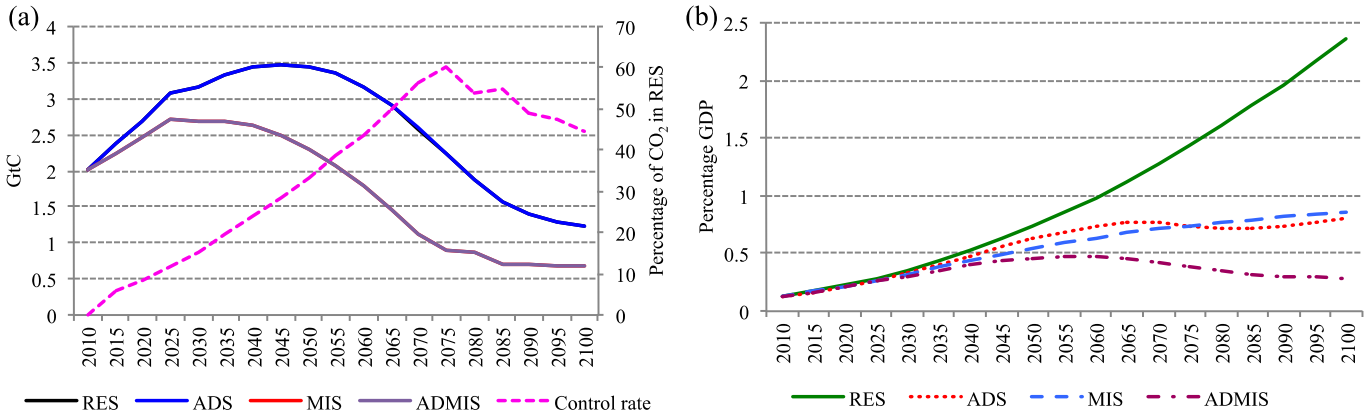

Fig. 6. Interactions between optimal adaptation and targeted mitigation in China's carbon emission trajectories (a) and dynamic residual damages (b).

facts: first, this case includes the energy efficiency improvement (EEI) measures during China Five-Year Plan from 2011 to 2015, and we assume this EEI process continues in the future, as a result, China's energy intensity in 2030 will decrease by 51.8% relative to the 2010 level; second, a default learning effect is taken into account for the development of renewables, especially wind energy, which makes its unit cost completely competitive before 2050 as compared to coal. This could largely explain the relative optimistic projections of emissions relative to those of RICE and WITCH models, but our results are greatly in line with the domestic mainstream studies (See Appendix C in SI for more discussions).

By introducing the 2-degree climate target, the emission trajectory moves down significantly, and the peak time advances to 2025, corresponding to a peak of 2.71 GtC. Because adaptation effort does not directly reduce carbon emissions, the emission paths with and without adaptation often overlap, as reported in Fig. 6-(a). In addition, the trajectory of the emission-control rate performs as 'hump' shape. To be specific, the strongest emission control occurs in approximately 2075, at which point the emission-reducing rate reaches 60%. After that, the strength of emission reduction weakens, and the corresponding emission-control rate will decrease to 44% by the end of this century. As we have mentioned, adaptation seldom affect emissions, so the emission trajectory under the portfolio policy case also overlaps with that under the pure mitigation case (Fig. 6-(a)).

Mitigation is an essential option to avoid climate damages. As sketched in Fig. 6-(b), the gross damages decrease by 26.1% in 2050 under the mitigation scenario, and by 2100, the damage-control rate will further grow to 63.9%. Through a comparison, we find that the residual damages under the adaptation case remain higher than that of mitigation case in the first half of the simulation period, but this situation changes after 2075, when the adaptation stock accumulates and adaptation efforts increase. In addition, in contrast to the adaptation or mitigation, the policy mix of both perform much better in avoiding climate damages, which is highly in line with the findings of de Bruin et al. (2009) and Agrawala et al. (2011). For instance, under the portfolio scenario, the residual damages account for only 0.46% of the GDP in 2050, versus 0.28% in 2100, which is largely lower than the results under the pure adaptation case, 0.51%, and under the sole mitigation case, 0.57%.

The changes in climate change costs (the sum of the residual damage, adaptation costs and mitigation costs) under the given scenarios can be observed in Fig. 7-(a). It is easy to find that the climate change costs in the presence of mitigation is significantly higher than that under the adaptation case, especially in the later period, which could be largely explained by the higher mitigation costs given the strict 2-degree warming control target. The introducing of adaptation in mitigation plays a negligible role in climate change costs, in spite of a subtle decrease by the end of this century (from 1.435% to 1.432%), which may mean that it is the mitigation cost that dominates the changes of climate change costs. Fig. 7-(b) to (d) report the ratios of cumulative benefits to costs under the pure adaptation scenario, sole mitigation scenario and portfolio scenario, respectively. Benefits in Fig. 7-(b) and (c) denote avoided climate damages resulting from adaptation and mitigation, respectively, while costs in this two subfigures mean adaptation investment and mitigation cost; and the total benefit in Fig. 7-(c) is the sum of adaptation benefit and mitigation benefit. As observed in Fig. 7-(b), adaptation gains the highest effectiveness in avoiding climate damages compared to mitigation and the mix of both. Although the adaptation costs remain larger than the benefits throughout the first half of simulation horizon, the ratio of benefits to costs increases significantly after 2050, and by 2100, this ratio approaches 2.

As a contrast, mitigation is an expensive way of avoiding adverse climate effects. As Fig. 7-(c) shows, the policy effectiveness of mitigation stays rather low during the entire simulation horizon. Even by the end of the 21st century, the corresponding ratio of cumulative benefits to costs is just 0.27. There are two points worth noting: first, the 2-degree warming rise target is actually much stricter than the INDC plans, which may undoubtedly lead to a higher policy costs, and our result estimates that the cumulative mitigation costs account for 0.97% of the total GDP; second, if a longer time period were to be considered, mitigation would promisingly become more beneficial and the cumulative benefit is likely to exceed the relative cost. Then the BCE of mitigation would increase significantly.

The expensive targeted mitigation causes the low policy effectiveness of the portfolio option, with the cumulative policy costs far higher than the relative benefits, despite the introduction of adaptation improving the BCE to some extent; our results indicate that even in 2100, the ratio of benefits to costs under the portfolio scenario is just 0.35 (Fig. 7-(d)). This implies that the cumulative climate benefits associated with adaptation will not only help to compensate the adaptation costs, but largely offset part of the mitigation costs. Combining the results of Fig. 7-(a) with those of Fig. 7-(c), we can observe that mitigation may become more benefit-cost effective in the long term, which should be largely explained by the inertia of the carbon cycle and climate system, the time-consuming process of economic restructuring and energy technology development and switching (Bréchet et al., 2013). As noted by de Bruin et al. (2009), the damage-avoiding benefit of adaptation remains much higher than that of mitigation, even in 2130, and after that, mitigation starts to reduce the bulk of damages. This implies that to successfully and earlier attain the point of effectiveness (i.e., the point at which the policy benefit begins to exceed the relative cost), earlier mitigation-related investment is urgently required. In addition, we ignore both spillover effects of other regions' mitigation and possible co-benefits resulting from carbon emissions reduction, which might lead to a remarkable underestimation of the mitigation benefits.

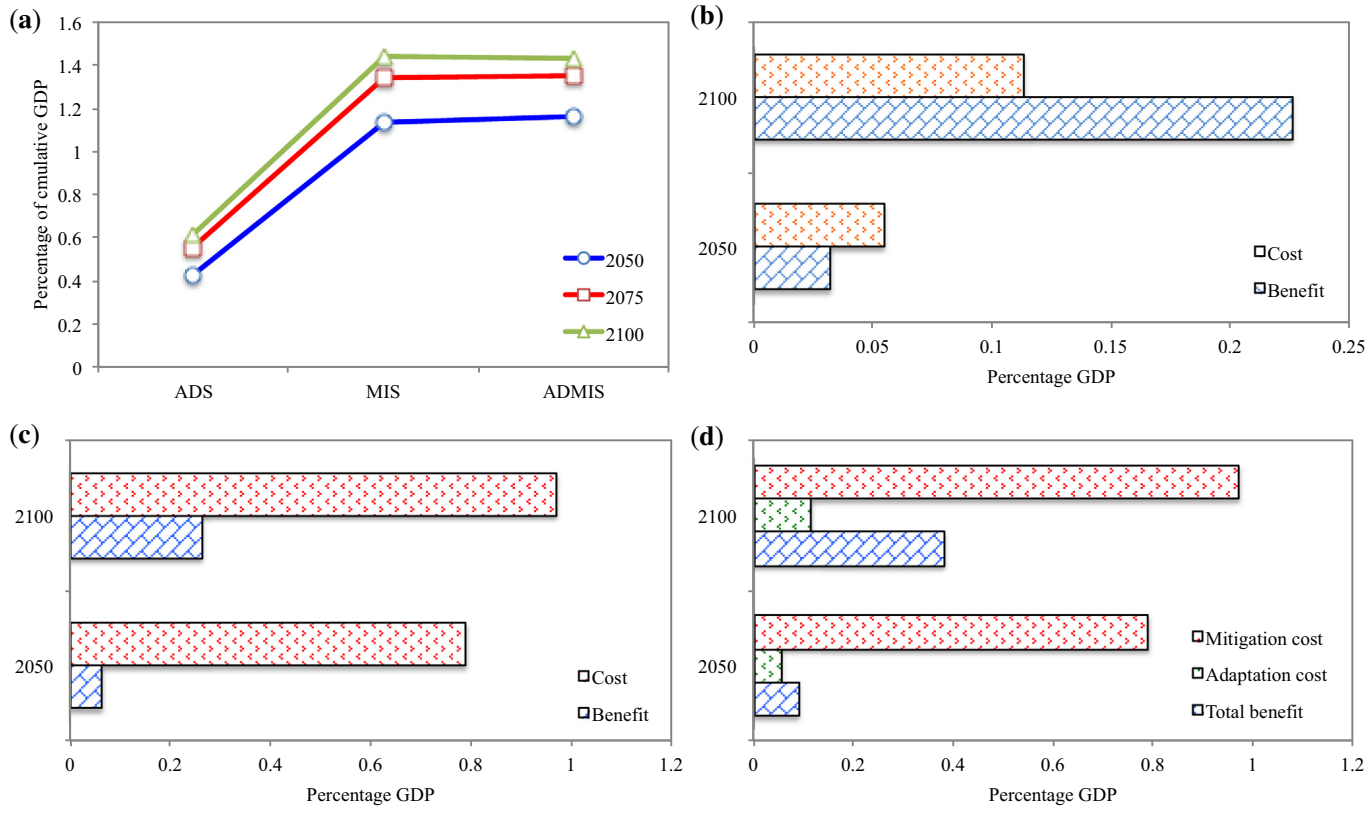

Fig. 7. Cumulative costs of climate change across various scenarios (a) and ratios of cumulative benefits to costs (b-d), corresponding to the adaptation scenario, the mitigation scenario and the portfolio scenario, respectively (we choose two time periods, i.e., 2010–2050 and 2010–2100, to accumulate the variables, with the discount rate assumed to be 5%).

4.3. Sensitivity analysis

4.3.1. Effects of the discount rate

The results and analysis of Sections 4.1 and 4.2 indicate that the BCE assessment of adaptation and mitigation depends heavily on consideration of the length of time periods, which in turn lies in the choice of the discount rate. On this ground, it is of great importance to check the robustness of the BCE of mitigation and adaptation to changes in the discount rate.

Overall, the effectiveness of all the targeted policy options will decrease as the discount level increases. It is therefore easy to infer that the lower the discount level, the higher the policy effectiveness. In addition, Fig. 8 shows that the policy effectiveness declines more significantly if mitigation intervention is implemented. This is because the effectiveness of mitigation always occurs in a longer period, which makes it suffer more from the option of discount rates. This finding has been verified by de Bruin et al. (2009) and Bosello et al. (2010), who argued that a higher discount level may cut down the effectiveness of mitigation, which in turn leads the option of the optimal climate policy to gradually transfer from mitigation to adaptation.

From time scales, the effectiveness of all the targeted policy increase as time passes, and this is robust to the discount levels. As for the adaptation scenario, by 2050, the highest benefit-cost rate is 0.67 given a discount rate of 3%. When moving to a time sale of 2100, the corresponding ratio increases to 1.48, even if a higher discount rate, 7%, is chosen. The mitigation benefits grow rapidly in the later period of our simulation, making the policy effectiveness more sensitive to the discount rates. For example, given a discount rate of 5%, the cumulative policy cost by 2050 is more or less the same with that by 2100, whereas the relative benefit by 2100 is many folds greater than that by 2050. As a result, the mitigation BCE by 2100 grows by at least 150% compared to that by 2050 (Fig. 8-(b)). As for the portfolio scenario, the cumulative policy benefit increases significantly and exceeds that under the sole mitigation case when extending the consideration of time periods, and the effectiveness of the mix policy approaches 0.5 given a discount rate of 3% (Fig. 8-(c)).

4.3.2. Effects of the damage curve coefficient

Coefficients of the damage curve are also critical sources of model uncertainty (Ekholm, 2018), especially for the coefficient of linear term (ζ_1) in the damage function; as shown in Table 1, different models remarkably differ in ζ_1. In this context, we design three scenarios to examine the BCE sensitivity to this parameter: 1) baseline scenario (Base × 1), keeping the parameter value assumption as depicted in Table 1; 2) high linear damage scenario (Base × 10), increasing ζ_1 from 0.0001 to 0.001; 3) higher linear damage scenario (Base × 100), further ascending ζ_1 from 0.001 to 0.01 (Fig. 9).

Through the aforementioned sensitivity analysis we could obtain three findings: first, linear term coefficient ζ_1 do has significant impacts on benefit-cost effectiveness of adaptation, mitigation, as well as the combined action; overall, a larger unit damage of linear trend causes a higher BCE of policy effort. Second, as compared to the other cases, BCE under the adaptation case is relatively more sensitive to ζ_1, moving from Base × 1 to Base × 100, the BCE of pure adaptation will increase from 2 to 6 throughout the simulation period. Third, the increasing of linear term damage has decreasing effects on BCE of pure mitigation, despite not so significant, and intervention of adaptation positively raise the sensitivity. This means that the BCEs of policy efforts are relatively stable with respect to dramatic changes of the linear damage coefficient, as for the most sensitive adaptation case, a hundred fold increase of damage coefficient only brings a three-time increase of BCE.

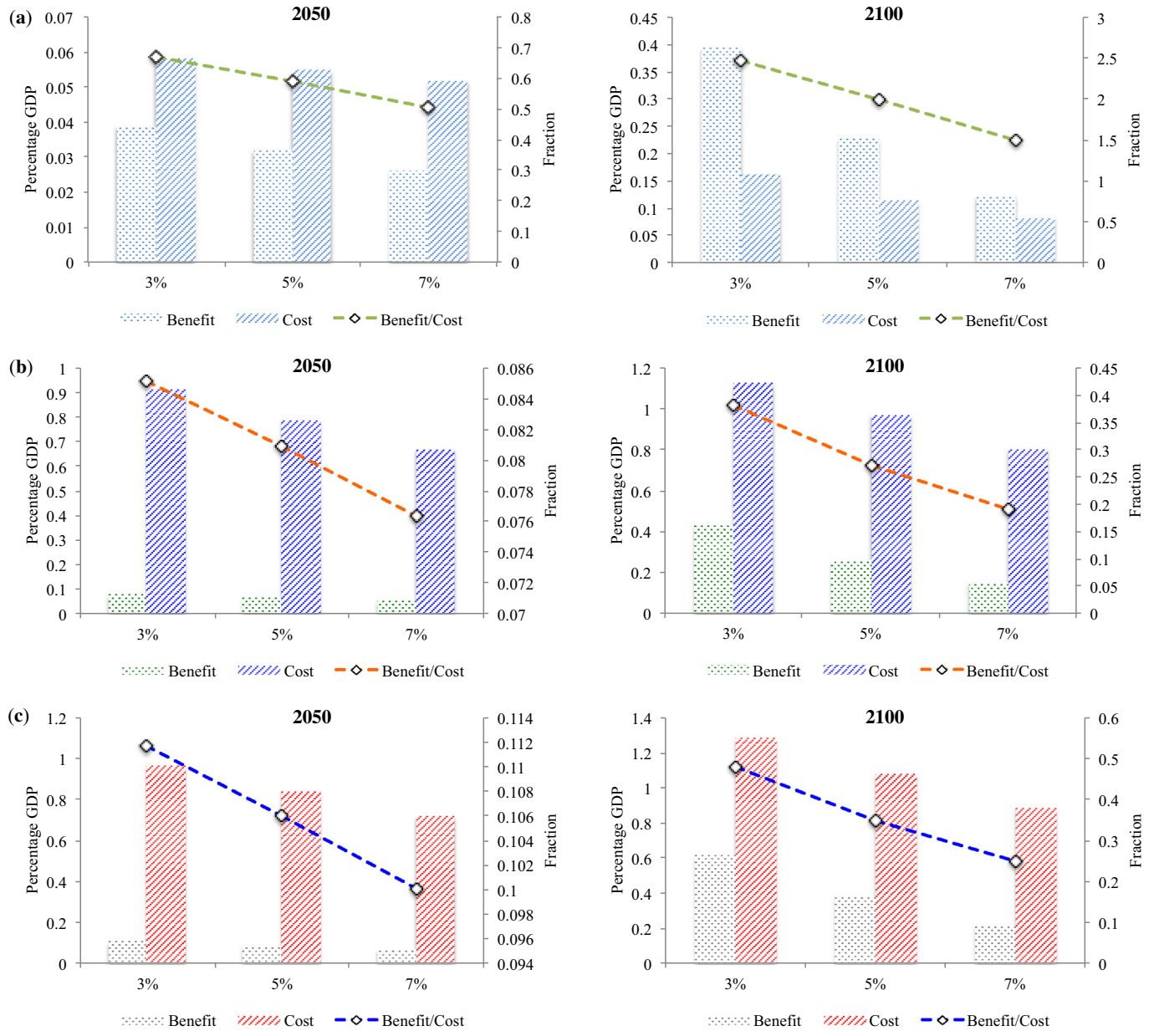

Fig. 8. Sensitivity of policy effectiveness to the discount rates. (a), (b) and (c) correspond to the adaptation scenario, mitigation scenario and the portfolio scenario, respectively (the left subfigure and right subfigure depict the results by 2050 and 2100, respectively).

5. Concluding remarks

This work contributes two aspects to the present literature: theoretically, we develop a climate change integrated model for China incorporating mature adaptation and mitigation mechanisms, and by combining it with the global E3METL, we build a complete framework to investigate the issues of regional climate damage assessment. Empirically, we successfully portray China's optimal adaptation cost curve and evaluate the dynamic effectiveness of optimal adaptation in the framework of benefit-cost analysis. In particular, we explore the impacts of mitigation intervention, given the Paris Agreement climate target, on the optimal adaptation and examine the role of discount levels and damage curve coefficients in policy effectiveness.

On average, optimal adaptation in China could avoid 28% of climate-related damages, with the highest damage-avoiding rate reaching 66%. It is worth noting that adaptation alone is far from enough to hedge against all the possible climate change risks, and our result supports that even though no adaptation restrictions are considered, the protection level resulting from adaptation is far from 100%. Similarly, mitigation alone cannot avert all the climate damages as well; in addition, the benefit-cost effectiveness of mitigation is significantly lower than that of adaptation, implying that in the short term, it remains true that adaptation is more benefit-cost effective than mitigation in response to climate damage reduction at the regional level, particularly for China. What needs to be emphasized is that the given Paris Agreement climate target, i.e., keeping the global temperature-rise from exceeding 2°C, is actually much stricter than the INDC plans, which should be largely responsible for the high mitigation cost and low short-term policy effectiveness. It can therefore be inferred that the policy BCE of mitigation would be greatly strengthened if the INDC plans were set to be the target. Further, the mitigation benefits associated with energy efficiency improvement and technological learning have already been included in the baseline case and could not been separately considered in this BCE analysis, which should tell another part of the story.

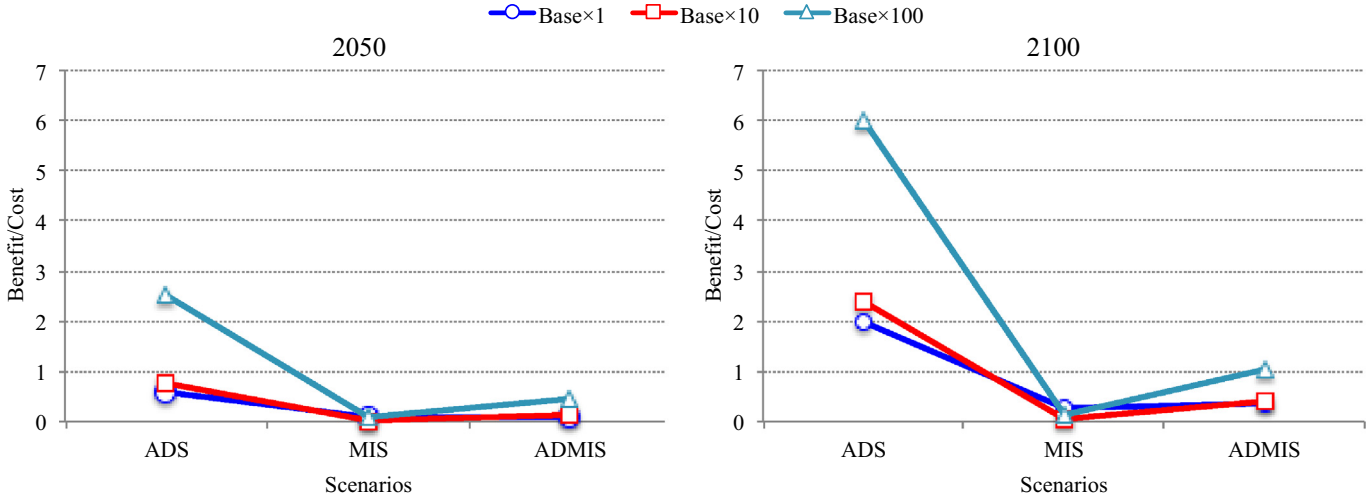

Fig. 9. Impacts of the key damage curve coefficient on policy effectiveness.

An important finding is that the effectiveness of a policy mix of adaptation and mitigation in response to avoid climate damages appears not to be '1 + 1 ≥ 2'. Actually, the policy benefits under the portfolio scenario are far lower than the sum under both the mitigation and adaptation scenarios but are still higher than any single policy scenario. Thus, there exists a negative interaction effect between mitigation and adaptation, owing to the possible crowd-out effect of investment. In contrast, the negative effect associated with mitigation intervention will be offset to a large extent by the increasing damage-reducing benefit associated with both mitigation and adaptation. As a consequence, the portfolio policy should still be the most fundamental option to cope with climate damage risks.

Through sensitivity analysis, we find that the choice of a discount rate significantly affects BCE of climate policies; generally, the lower the discount level, the higher the policy effectiveness and vice versa. In particular, the intervention of targeted mitigation reinforces the effect of the discount level, which supports the related conclusions of de Bruin et al. (2009) and Bosello et al. (2010); that is, compared to adaptation, effective mitigation is more likely to occur in a longer time period. Thus, when we systematically assess the effect of climate policy, two important co-existing factors must be considered: policy effectiveness and time scales. The former closely relates to the policy benefits and costs, which are the centers of focus of both decision-makers and the public. Generally, only the policy option with relatively higher benefit-cost effectiveness, i.e., with the maximal potential ratios of benefits to costs, is predominant and more likely to be implemented. Additionally, the definition of the latter significantly influences the assessment of policy effectiveness, particularly for mitigation and adaptation, for which the choice of a discount rate plays a formidable role.

It is worth noting that there are some uncertainties on BCE assessment of mitigation in this work. On one hand, we only take into account direct mitigation benefits under the global 2-degree warming-stabilizing goal, while leaving out the trade-offs between spillover effect of China's targeted mitigation and that of the rest of world, which should be of importance to assess policy effectiveness of mitigation at the regional level (Duan et al., 2018). To address this issue requires a geographically extension of E3METL, distinguishing China from the rest of world. On the other hand, we ignore the potential other co-benefits associated with emissions control; in effect, co-benefits of mitigation, such as enhancement of energy security and improvement of local air pollution, has been widely found in recent studies (Jewell et al., 2016; Rao et al., 2016). As a consequence, the mitigation BCE assessed in this work might be underestimated to some extent. In fact, systematical assessment of co-benefits associated with mitigation opens an interesting and extensive research agenda, which should be one of focuses of our future study. Lastly, substantial empirical estimates on the effects of climate change on China's economy are urgently needed, which greatly helps to equip our damage function and explore the long-term integrated assessment of climate damages.

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Appendix A. Supplementary information

Supplementary information to this article can be found online at https://doi.org/10.1016/j.ecolecon.2019.02.008.

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